

# PartNet: A Large-Scale Benchmark for Fine-Grained and Hierarchical Part-Level 3D Object Understanding

Notes and Relevance for Game Affordance Mapping Project

**Source:**

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## 1. Overview

PartNet is a large-scale dataset of 3D objects annotated with detailed, instance-level, and hierarchical part information.

It enables fine-grained geometric analysis, object understanding, and data-driven reasoning about how objects are composed and function.

**Dataset Statistics:**

- **Total Models:** 26,671 3D shapes
  - **Part Instances:** > 573,000
  - **Categories Covered:** 24 (e.g., chair, table, bed, lamp, door, cabinet, bag, etc.)
  - **Base Source:** Built on top of ShapeNetCore, extending it with detailed semantic part annotations
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## 2. Purpose and Contribution

PartNet was developed to address a gap in 3D vision research: most existing datasets had object-level labels but lacked consistent, fine-grained, and hierarchical part-level annotations.

**It supports the study of:**

- Fine-grained shape analysis
- Hierarchical semantic reasoning

- Dynamic scene understanding
  - **Affordance and functionality learning** (relevant to this project)
  - 3D shape generation and simulation
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## 3. Dataset Structure

Each object model in PartNet is represented with:

### 3D Mesh Geometry

- Full-resolution mesh from ShapeNetCore
- Stored in .obj format (triangular faces)

### Hierarchical Part Annotations

- Labels structured in a tree hierarchy (e.g., chair → backrest → slat)
- Enables learning at multiple semantic levels

### Instance-level Segmentation

- Distinguishes between repeated components (e.g., 4 legs of a chair)
- Facilitates instance-aware learning

### Fine-grained Semantic Labels

- Consistent naming across models (e.g., "seat," "handle," "drawer front")
  - Supports high-level reasoning about functionality and design
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## 4. Benchmarking Tasks

The authors propose three benchmark tasks to evaluate 3D part-level understanding:

Task	Goal	Output Type
<b>Fine-Grained Semantic Segmentation</b>	Assign each point or face a fine-grained part label (e.g., seat, handle, drawer)	Per-point or per-face labels
<b>Hierarchical Semantic Segmentation</b>	Predict multi-level part labels consistent with the annotation hierarchy	Hierarchical label tree

<b>Instance Segmentation</b>	Identify distinct instances of repeated parts (e.g., four chair legs)	Instance IDs per part
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## 5. Proposed Baseline Method: PointNet++

The original paper establishes baseline performance using **PointNet++**, a hierarchical neural network that processes point clouds rather than meshes.

Each 3D object mesh is sampled into a point cloud (~10k–50k points), where each point inherits its part label.

### Key Features of PointNet++:

- Operates directly on unordered point sets
- Learns local geometric features using hierarchical sampling and grouping
- Robust to input permutation and varying density
- Efficient for large-scale datasets like PartNet

**Relevance:** This is directly relevant to the Game Affordance Net hybrid pipeline, which uses **DGCNN (Dynamic Graph CNN)**—a successor model that builds on the PointNet++ philosophy but adds dynamic local graph learning for improved shape understanding.

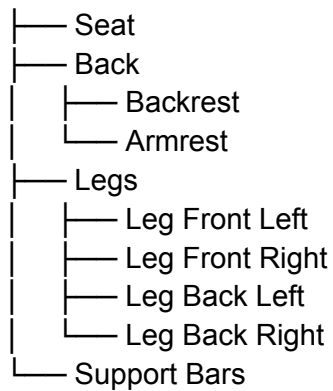
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## 6. Dataset Hierarchies and Label Example

Each object category has a predefined semantic hierarchy.

### Example: Chair

Chair



This structure allows models to reason about:

- **Object composition** (how parts fit together)
  - **Functional affordances** (how those parts relate to human actions)
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## 7. Technical Details

### Data Format:

Each object includes:

- `.obj` mesh file
- `.json` annotation tree with part hierarchy
- `.pts` or `.ply` sampled point cloud with per-point labels

### Label Schema:

- 337 fine-grained part categories organized across 24 parent object types

### Sampling Strategy:

- Uniformly sampled 3D points from mesh surfaces, maintaining consistent coverage for dense labeling

### Annotation Process:

- Human annotators manually labeled parts through a web-based 3D annotation interface, ensuring high accuracy and consistency
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## 8. Dataset Usage in This Project

### Integration with Hybrid Point–Mesh Pipeline

For the affordance learning system, PartNet provides both the geometry (mesh) and semantic part labels needed to train supervised models.

### Training Data Preparation Workflow:

1. Load the PartNet mesh for each object

- 2. Sample 20–50k surface points
- 3. Inherit the part label from the original annotations
- 4. Map part → affordance (e.g., seat → sit, handle → grasp, shelf → support)
- 5. Train DGCNN for per-point affordance segmentation
- 6. Project predicted affordance labels back onto the mesh for Unreal integration

This enables the model to learn **shape-to-function mapping** — understanding how geometry implies possible actions.

## 9. Why PartNet Is Suitable

Criterion	Relevance
Large Scale	Over 500k annotated parts across 20k+ shapes ensures generalization
Fine-Grained Detail	Essential for detecting affordances that depend on small geometric variations (e.g., handle vs. rim)
Hierarchical Labels	Supports multi-level affordance reasoning — local vs. global object function
Consistency	Standardized annotation schema across categories supports cross-object learning
Public Benchmark	Widely used in recent research (PartAfford, SegAffordSplat, MeshPointNet), ensuring compatibility with state-of-the-art pipelines

## 10. Relevance to Affordance Research

PartNet is not an affordance dataset by itself—it provides **structural and semantic part annotations** that can be mapped into affordance categories.

### Example Mapping:

Part Label	Mapped Affordance
Seat	Sit
Handle	Grasp
Drawer	Pull

Basin	Contain
Shelf	Support
Button	Press

This mapping acts as the **supervised training signal** for affordance detection models such as DGCNN.

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## 11. Related Datasets and Extensions

Dataset	Focus	Relation to PartNet
<b>PartNet-Mobility</b>	Adds motion and articulation (e.g., open/close)	Useful for dynamic affordances
<b>ShapeNetCore</b>	Object-level 3D models	Parent dataset
<b>PartAfford</b>	Maps PartNet labels to affordance labels	Directly relevant
<b>Shape2Motion</b>	Adds kinematic information	Enables learning of movable parts

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## 12. Summary

- PartNet provides the **semantic and geometric foundation** for affordance learning
- It enables training data creation through **part-to-affordance mapping**
- Supports **dense point cloud segmentation**
- Serves as the benchmark for evaluating 3D understanding
- Its integration into the **hybrid pipeline** (point-based DGCNN → mesh projection → Unreal tag import) directly supports the automation of geometry-aware affordance detection in 3D game environments